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Urban Social Disorder: An Update

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Contents

1. Introduction

Despite a worrying uptick in political violence in recent years, the post–Cold War period has seen a noticeable and much-lauded decline of war (Goldstein 2011; Pinker 2011). Indeed, conflict-related casualties have been on the decline since World War II (Gleditsch et al. 2002; Lacina et al. 2006). Important contributors to this downward trend are a reduction in large-scale wars between states, the end of decolonization wars and superpower rivalry, peaceful resolutions of rural insurgencies in Latin America, and the transformation of Southeast Asia from a place of revolution to a stable economic powerhouse.

While popular uprisings in the Middle East and North Africa and the spread of militant ideology have contributed to a temporary reversal of this trend, other societal forces of a more permanent kind may have a more lasting imprint on the nature and trajectory of future conflict. Perhaps the most important among these forces is the rapid demographic transition of the developing world from being largely rural to being predominantly urban. This shift likely implies a transformation of political violence as well, where conventional and organized rural insurgencies – the dominant form of armed conflict today – will be gradually replaced by less organized urban upheavals and urban terrorism.

Existing efforts to catalogue detailed information about conflict events, such as the Armed Conflict Location and Event Dataset, ACLED (Raleigh et al. 2010), the Social Conflict Analysis Database, SCAD (Salehyan et al. 2012), and the Uppsala Conflict Data Program's Georeferenced Event Dataset, UCDP GED (Sundberg and Melander 2013), while highly useful and revealing in many regards, only cover the post–Cold War period and are therefore unsuitable to detect systematic, longer-term changes in patterns of urban political violence.

As an alternative, we provide an updated version of the Urban Social Disorder (USD) dataset. Whereas the initial version of the USD data (Urdal and Hoelscher 2012) contained information about urban unrest in 56 major cities in Sub-Saharan Africa and East / Southeast Asia, 1960–2006, the updated version adds another 47 urban centers covering the Middle East, North Africa, and Latin America.[1] Moreover, all cities have been updated throughout 2014, implying that USD v.2.0 includes data on lethal and non-lethal disorder events for 103 cities in 89 countries across the developing world for the past 55 years.

This paper consists of four parts: The first two sections present the new dataset and describe some simple patterns of urban social disorder in space and time. The subsequent section provides a graphic comparison of USD with three commonly used conflict event datasets: ACLED, SCAD, and UCDP GED. In the fourth section, we conduct a reanalysis of a published study of urban population growth and social disorder as a test of whether earlier findings, based on the original version of the USD dataset, are likely to hold up with updated and expanded data.

[1] The initial version of the USD dataset collected data on 56 cities. However, it should be noted that one of these cities had no disorder events, so only 55 cities are represented in the actual dataset.

2. About the Dataset

The USD dataset is an event dataset of major cities globally. Specifically, it covers all capital cities of above 100,000 inhabitants, including any city that was once a capital in the period since the start of the dataset (1960). In addition, selected major non-capital cities were also included. The non-capital cities fall into two categories. The first includes cases where the capital city is considerably smaller (defined as less than 50% of the population size) than the largest city in the country. An example would be Nigeria, where the capital, Abuja, is considerably smaller than Nigeria's by far largest city, Lagos. In such cases we have covered both the capital and the largest city.[2] For some major countries (China, India, Brazil) with multiple mega-cities, we have coded additional, select major cities.[3]

Consistent with the initial version of the Urban Social Disorder dataset (Urdal and Hoelscher 2012), version 2.0 contains records of unrest events coded from electronic news reports in the online version of the Keesing's Record of World Events. Keesing's is a highly regarded and widely used resource of information on political events. As a news aggregator, they publish yearly, event-specific, and monthly summaries of news of political, economic and social significance from across the world, based on a variety of news sources. As such, the USD dataset suffers from the same general challenges that most event datasets using news sources have to face. While news reports are likely to cover all events of major political significance, there are potentially important biases in event data that need to be carefully addressed, particularly when analyzing cross-sectional (between geographical areas) and time-series trends (see Text Box 1).

Text Box 1. Biases in news-based event data

First, strong and autocratic regimes may to some degree succeed in censoring information about events that are considered undesirable, preventing events from entering into news sources such as those used by Keesing's. At the same time, such regimes are probably also relatively successful in preventing undesirable political events from happening. However, distinguishing between bias and regime effect is inherently difficult.

Second, the consumers of news sources such as Keesing's, which are primarily institutions and individuals based in the developed world, may take a stronger interest in certain geographic areas than others, influencing the news providers' priorities of what areas to cover in greater detail. Hence, events happening in countries that are low on the international agenda are possibly less likely to be reported than similar events in countries of high political and economic strategic importance.

Third, it is possible that improvements in communications technology and greater international presence in more places generally means that more events are being reported by international media. Hence, it is difficult to assess whether a general increase in the number of events reflects more events, or just better reporting. Fourth, reporting biases may differ over time for different areas as certain regions wane in economic or geopolitical importance over time, and others wax. While these biases are not easily corrected, students of event data based on news sources need to be alerted to these potential shortcomings.

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[2] Note that in a small number of cases where the formal capital is not the *de facto* capital, such as Dodoma, Tanzania, the de facto capital is coded (in Tanzania: Dar Es Salaam).

[3] These additional cities include Shanghai (China), Sao Paolo and Rio de Janeiro (Brazil, both coded in addition to the capital, Brasilia), and Mumbai and Calcutta (India).

All electronic searches were done manually by human coders, using a specific set of search procedures to highlight terms associated with political violence and disorder. In determining relevant events, urban social disorder was understood to encompass social actions directed against a political target and challenging political authority. Actors may vary considerably in terms of organization, number of participants, use of (non-)violence, and type of political target. Relevant events include demonstrations, rioting, terrorism, and military battles. USD events are separable from crime in that they are politically motivated, and although that distinction is sometimes blurred, an event is considered relevant if the nature of the target is political.[4] Moreover, as this is a city-specific dataset, only events that took place within the official perimeters, suburbs, or immediate outskirts of the selected cities are included in the dataset.

For all relevant events, the dataset contains information on the location, type of event, start and end date, actor(s) and target(s), the reported number of affected individuals or participants, and the reported number of deaths. If a series of events involving the same actors and targets happened within a short period of time, this would normally be coded as one event (e.g. several bombs against government targets happening within few days). If events involving the same actors and targets are spaced by at least one week (seven days), they would normally be coded as different events. At times, a report will summarize a collection of events happening over a long time period, such as a period of continuous demonstrations or battle-clashes lasting for several months. In the absence of information about each individual event, these aggregated events are recorded as one long event.

Finally, it should be noted that the 12 different 'problem types' (see Table 1) that all events are categorized under are by no means mutually exclusive categories. Demonstrations that are initially peaceful may develop into riots, and the activities of armed opposition groups may in one context (and one time period) be labeled rebellion, and in another, terrorism. In cases where events escalated from one problem type to another, we coded the events at the highest level of severity. While we have tried to be consistent in the coding of such events, one should be careful in treating the categories as clearly distinguishable phenomena. The provision of the text extracts allows researchers to overrule the current coding of types by going into individual cases carefully.

See Urdal (2008), Urdal and Hoelscher (2012), and Bahgat, Buhaug, and Urdal (2017) for further definitions and details on coding procedures.

[4] An example of a type of event that is not included is clashes between the police and gang members, since this is arguably part of an ordinary process to uphold order and security, unless there is evidence to the contrary. For similar reasons, prison riots were not coded, even if the rioters were mainly political prisoners aiming to make a political statement. On the other hand, we code clashes between police and political groups, or politically motivated attacks on prisons from the outside.

3. Trends in Urban Social Disorder

The original USD dataset contained records of 3,375 disorder events in 55 major cities in 49 countries across Sub-Saharan Africa and East and Southeast Asia, 1960–2006 (Figure 1). These are mostly capital cities, although the project additionally collected information for a limited number of mega-cities. In the new version, the geographic scope has been vastly expanded. USD v.2.0 covers 103 cities in 89 countries: almost every capital city in the developing world as well as a limited number of other major cities. The temporal scope has also been expanded and now covers all years, 1960–2014. In total, the new version contains records of 9,018 events.

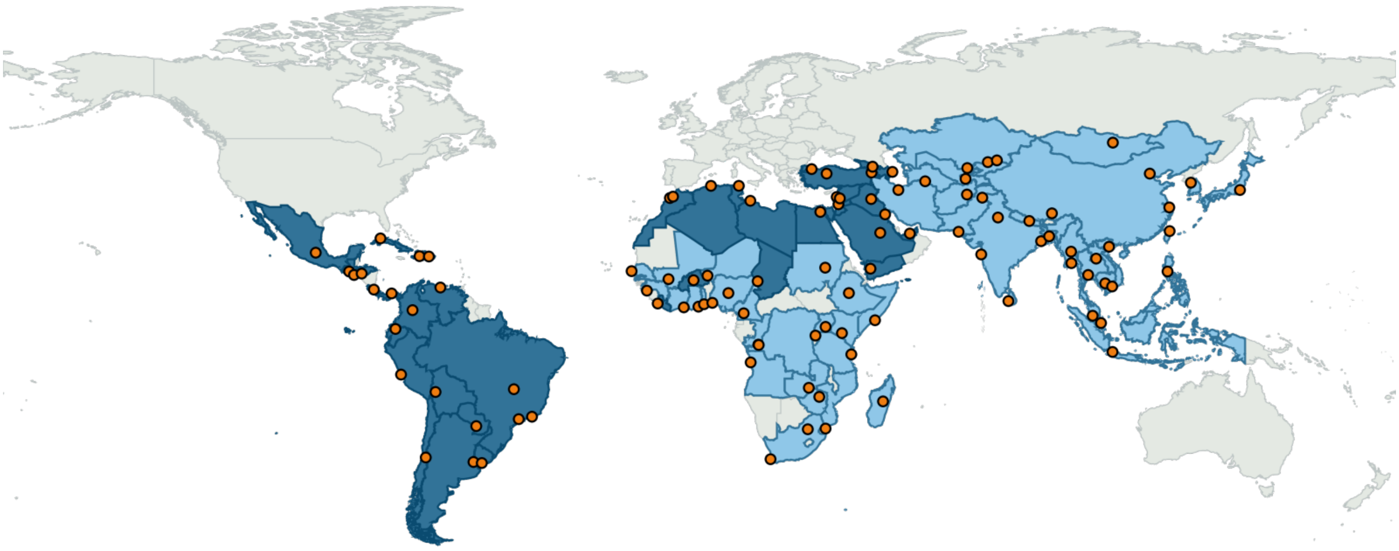

Figure 1. Geographic coverage of the Urban Social Disorder datasets

Note: The map shows the geographic coverage of the Urban Social Disorder dataset. Orange symbols denote the location of the cities included in the complete dataset. Light blue countries reflect the coverage of the first original (USD v. 1.0) whereas dark blue countries have been added in the USD 2.0 update. Light gray countries are not covered.

The USD dataset separates between 12 event types (Table 1). The dominant form of disorder is organized demonstrations (25.2%), followed by armed attacks (19.7%). In contrast, at 66 events, inter-communal warfare makes up only 0.7% of all events, owing both to the general rarity and the mostly rural nature of such conflicts. Figure 2 visualizes the distribution of events among the sample cities, and Figure 3 demonstrates how disorder in selected cities has evolved over time. Much as one would expect, the cities with the highest rates of unrest are located in countries with significant instability and turmoil. The city with the highest number of recorded events is Baghdad with 473 events, even though it was relatively calm until the US-led intervention and subsequent fall of the Saddam Hussein regime in 2003. Conversely, Beirut lived through most of its upheavals in the 1980s and has seen little disorder in recent years. Even though the top eight most affected cities account for more than a quarter of the total number of recorded events, the distribution of urban social disorder is relatively even among the sampled cities.

Table 1. Type and frequency of urban social disorder events

Event type	Frequency
10 General warfare	394
20 Inter-communal warfare	66
30 Armed battle/clash	442
31 Armed attack	1,778
40 Pro-government terrorism (repression)	409
41 Anti-government terrorism	1,080
42 Communal terrorism	579
50 Organized violent riot	319
51 Spontaneous violent riot	1,026
60 Organized demonstration	2,275
61 Pro-government demonstration	165
62 Spontaneous demonstration	485
TOTAL	9,018

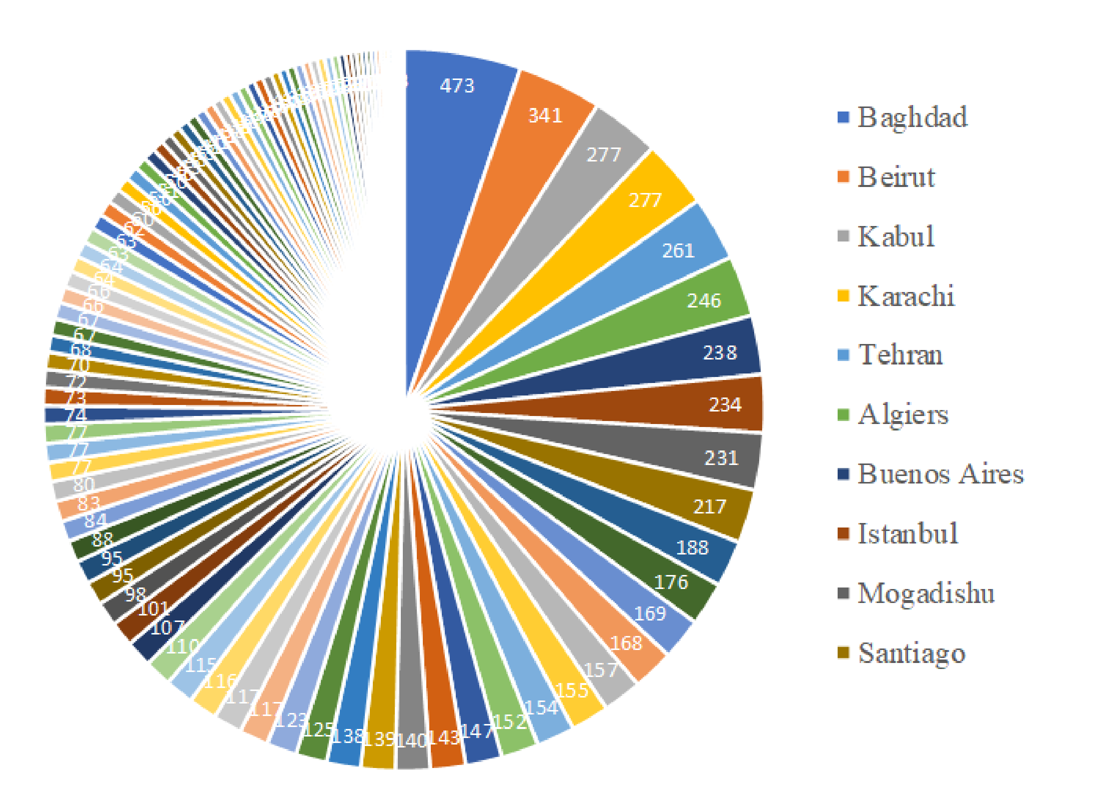

Figure 2. Distribution of urban social disorder events among cities

Note: The pie chart shows the total number of disorder events by city, 1960–2014. The identified cities on the right reflect the top-ten list in ranked order.

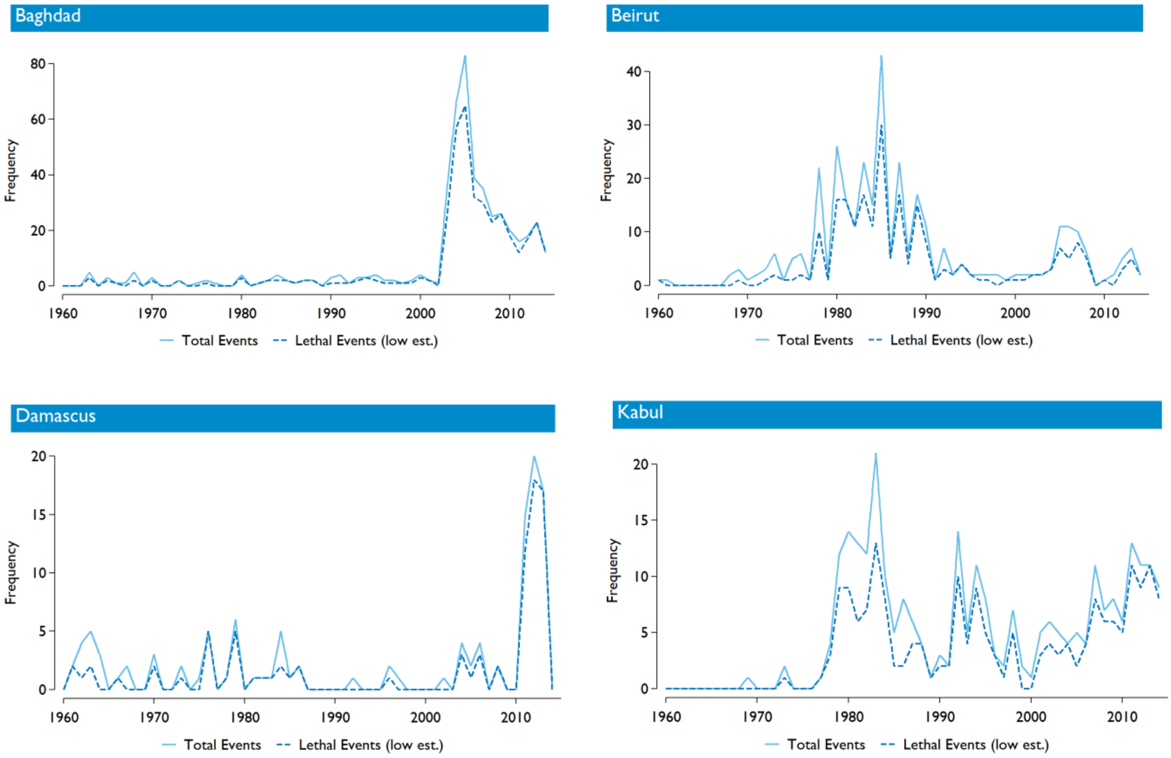

Figure 3. Urban disorder events for select cities, 1960–2014

We began this paper by referring to the well-known decline of war and speculated whether the ongoing demographic shift towards increasing concentrations of people in urban centers will lead to a similar transition of political violence. The left panel of Figure 4 would seem to give support to such reasoning. With the exception of a few unusually calm years around the turn of the century, the prevalence of lethal as well as non-lethal events has been rising steadily over time. Just like Urdal and Hoelscher (2012) reported for the first version of the USD data, the total average of annual number of disorder events in major cities of the developing world has roughly doubled over the past sixty years.

However, if we instead focus on the severity of these disorder events in terms of number of reported fatalities (right panel), there is no apparent temporal trend that would be consistent with a general shift from rural to urban violence.[5] Instead, the trend in urban social disorder casualties exhibits significant fluctuation, driven by sporadic occurrences of very violent events. Interestingly, the recent increase in the number of civil conflicts and battle deaths (Melander et al. 2016) is not reflected in the USD data. While the USD dataset includes Syria (Damascus), Iraq (Bahgdad), and Afghanistan (Kabul), which accounted for more than half of all civil war-related deaths in 2015, most of the battles in these conflicts took place elsewhere in the respective countries. Note also that due to poor or unclear information, some events in the USD dataset are likely to suffer from significant undercounting of casualties.[6]

[5] The casualties estimates as well as the classification of events as lethal or non-lethal in Figure 3 are represented as a range to reflect uncertainty in the USD data. The lower band of the lethal events (left panel) assumes that all events with unknown deaths were non-lethal whereas the upper band assumes that they caused at least one casualty. To avoid outlier bias and ease interpretation, Kigali, 1994 (the Rwandan genocide) was excluded before generating the casualty trend (right panel).

[6] In the USD dataset, many events are listed with the lowest possible threshold only, such as >0 or >100, for instance when news reports refer to deadly events but fail to provide an estimate, or when reports give estimates only for specific incidents within a protracted multi-day event. In the absence of precise information, the USD dataset records the lowest and most conservative figure, implying that the true casualty figures are sometimes much higher than indicated in these data.

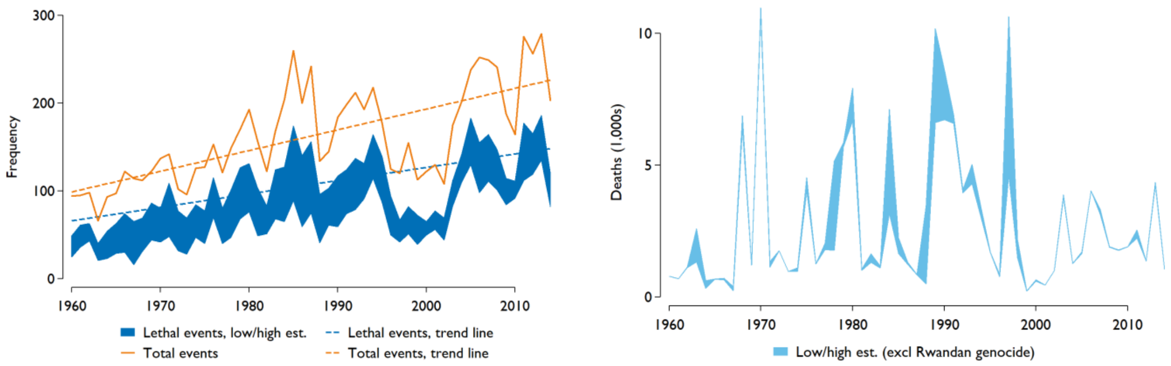

Figure 4. Frequency and severity of urban disorder events, 1960–2014

Another way of looking at the data is in the context of broader population trends. An increase in urban disorder might not be that surprising given that we live in a world where an increasingly large proportion of the population are moving to and living in the cities. When expressed as the rate of events per 100,000 inhabitants in the sample cities, urban disorder has steadily decreased by about one-third since 1960 (see Figure 5).

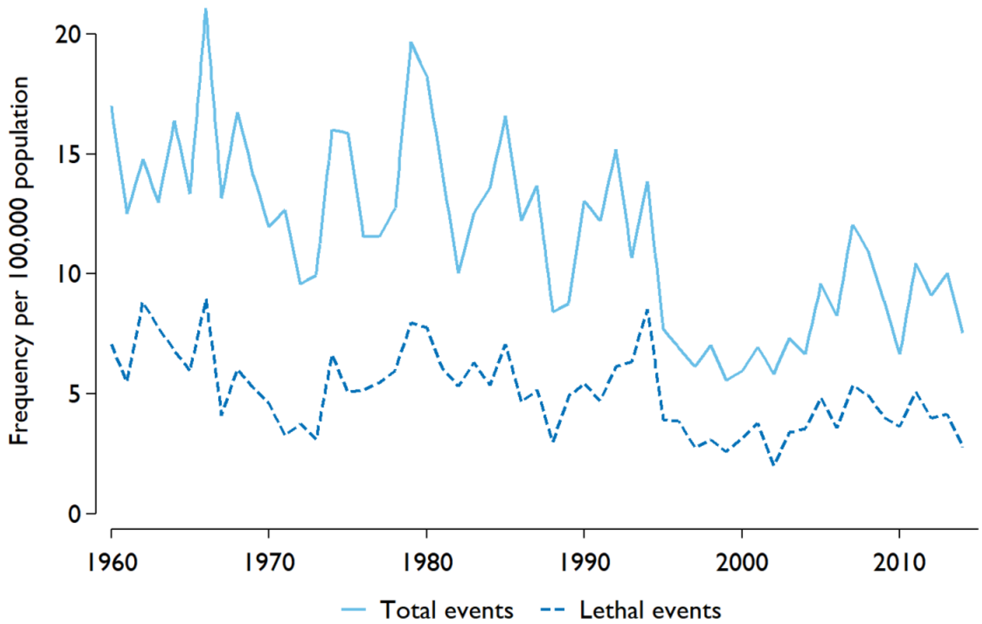

Figure 5. Population-adjusted frequency of urban disorder events, 1960–2014

The aggregated trend in disorder events masks some interesting inter-regional variations (Figure 6). While the overall increase in events may be detectable in Asia, the Middle East, and Africa, Latin American unrest differs with its distinct bell-shaped distribution, peaking during the ravaging civil wars of the 1980s. Also detectable in some, but not all, of the regional graphs are the two waves of social uprisings during the global financial crisis and food price shocks (2007–8 and 2010–11), the latter of which included the Arab Spring events. Another pattern that varies between these regions is the relative distribution of lethal versus non-lethal disorder. In Asia and Sub-Saharan Africa, less than half of the events involved at least one death, whereas in Latin America and the Middle East almost all reported episodes of social unrest were deadly. Figure 7 shows a similar graph for people reportedly affected by these events and clearly reveals the massive impact of the Arab Spring uprisings on the Middle East and North Africa.

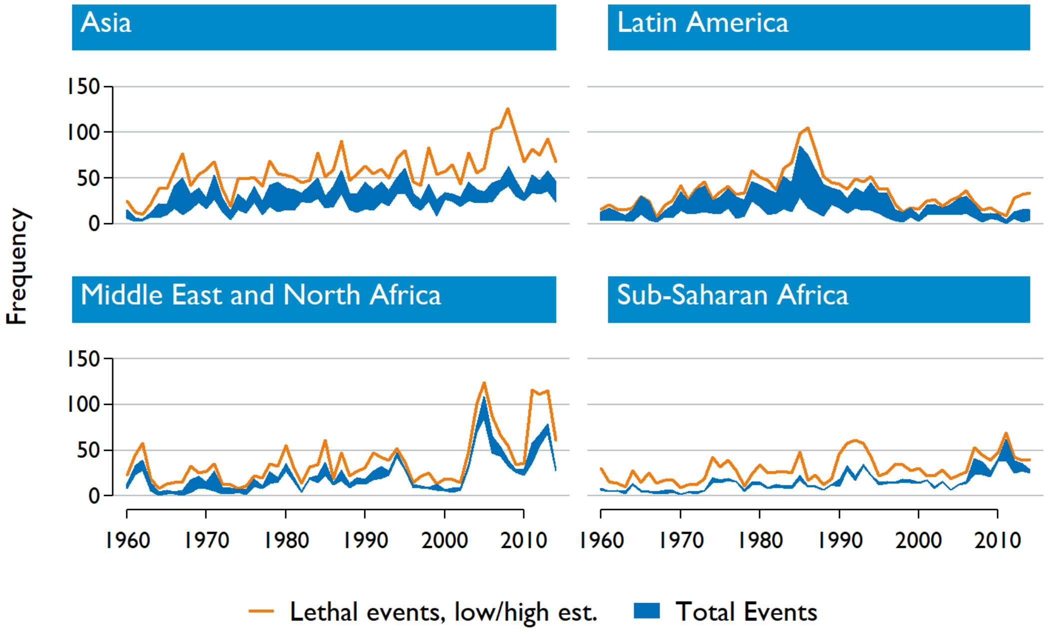

Figure 6. Regional trends in urban disorder events, 1960–2014

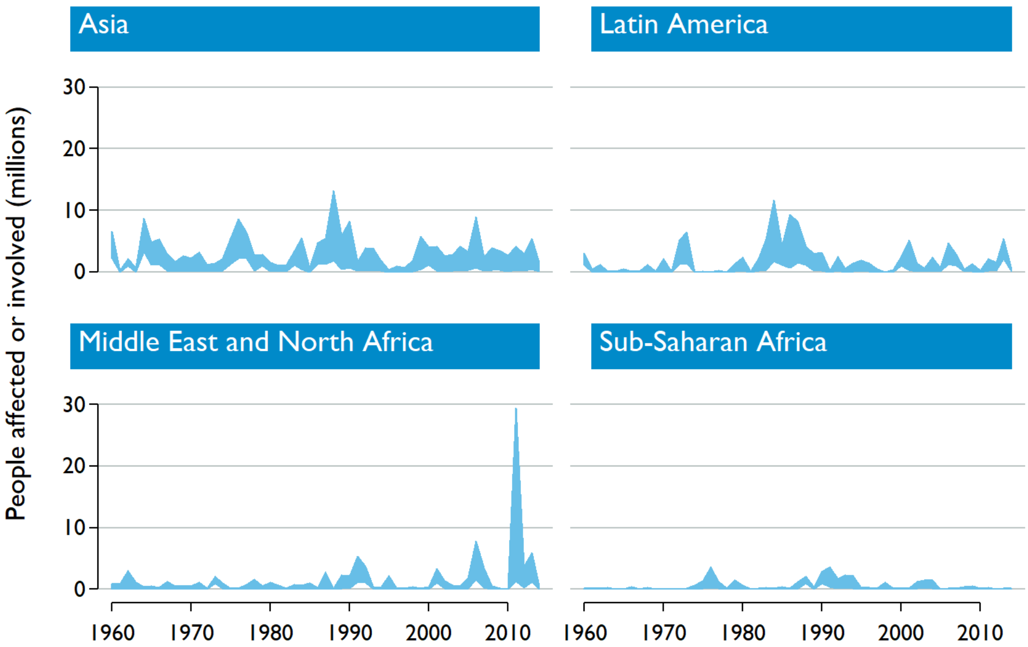

Figure 7. Regional trends in people affected by urban disorder events, 1960–2014

As a final documentation of the patterns in the USD 2.0 dataset, Figure 8 visualizes the trends in the data broken down by event type. Reflecting the descriptive statistics provided in Table 1 above, we see considerable variation in prevalence between forms of social action. Even so, the temporal patterns are quite similar among the most prevalent event types, with a slow but relatively predictable increase in disorder frequency. The most distinctive break from that pattern is found among organized anti-governmental demonstrations, especially lethal ones, which reached their highest peak during the collapse of the Cold War system.

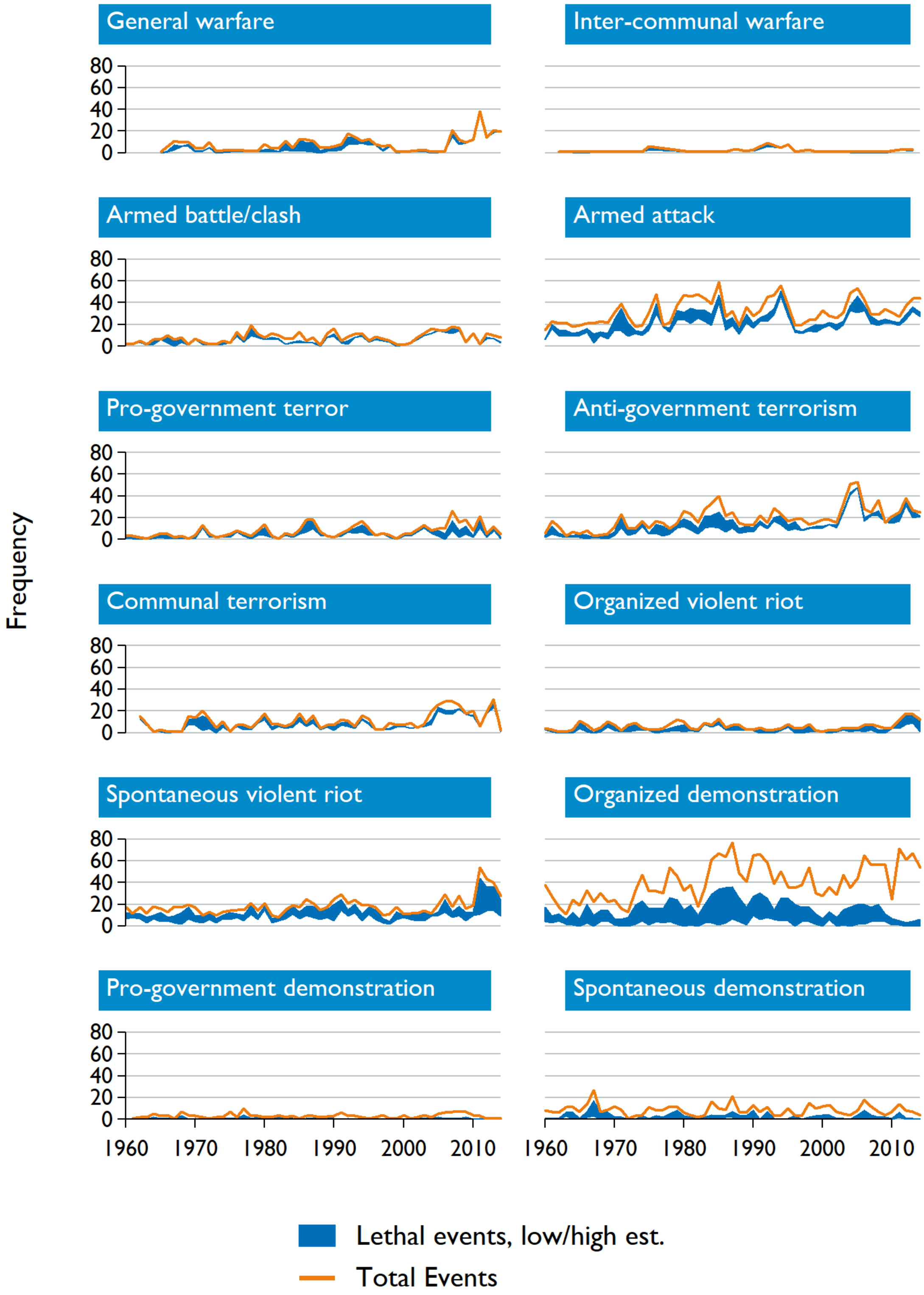

Figure 8. Urban social disorder events by type, 1960–2014

4. Comparison with Other Conflict Event Datasets

The Urban Social Disorder dataset is the only city-specific collection of unrest that spans the developing world across more than half a century. ACLED, SCAD, and the UCDP GED datasets, similar in some ways to USD, cover many of the same types of events and they are not limited to capitals and other major cities. However, while these datasets offer a broad scope in terms of geographic coverage and draw on a greater variety of news providers, they only go back to the 1990s and, with the exception of the latest version of UCDP GED, only cover some parts of the developing world.[7]

Where the USD dataset contributes is in its more detailed focus on single cities, sampled across a large set of relevant countries and over a comparatively long time period. However, collecting information on events occurring well before the digital information age poses significant challenges. Media coverage and quality of reporting have improved markedly over time, so the likelihood of a given event being picked up by Keesing's, the sole source used in USD, is partly a function of when it happened. For example, older reports often describe aggregations of events and sometimes review developments during an entire year in one article. Recent reports, in contrast, give updates more regularly for each month. For this reason, some of the documented increase in urban disorder may be due to reporting bias. While the USD dataset thus cannot make claims about completeness, we believe it offers sufficiently representative estimates to allow for longitudinal as well as comparative analyses.

To assess the extent of correspondence in spatial and temporal trends with other data sources, we selected the most recent versions of ACLED, SCAD, and UCDP GED and matched events from these datasets with the USD data based on city names. For simplicity, we consider all event types in these datasets – drawing subsets in an effort to directly compare similar event types is potentially also possible but presents a different set of challenges since the datasets use different definitions and differ on other dimensions beyond event types (e.g., definition of relevant actors, minimum severity threshold, and procedures for handling unclear cases).

Figures 9–11 compare aggregate trends in USD events with similar trends for ACLED, SCAD, and UCDP GED, respectively. Each graph compares both total number of events (left side), and number of lethal events with at least one death (right side). Each figure is limited to cities that are covered by both data sources. We do not attempt to filter the data by event type; each graph shows the total count of event by year for overlapping cities.[8] Since ACLED only covers Africa for the temporal domain of the USD data (1960–2014), the trend lines in Figure 9 applies to African cities only. Figure 10 is limited to SCAD's coverage of cities in Africa plus a handful of Central American cities, whereas Figure 11 is based on the full USD sample (minus Damascus), owing to the global coverage of the UCDP GED dataset.

Despite (or perhaps partly because of) ACLED's limited spatiotemporal domain, we see that this dataset contains a higher number of recorded conflict events than any of the other datasets considered here. This is certainly also because ACLED collects information on several types of

[7] Specifically, ACLED is limited to Africa (1997-) and parts of Asia (2015-) whereas SCAD covers Africa, Mexico, Central America, and the Caribbean (1990-).

[8] Significant differences in sample inclusion criteria in terms of actor definitions, minimum severity threshold, and how to code events that span multiple days or weeks add to the difficulties of making a direct, side-by-side comparison of the same event types (though see Eck 2012).

incidents that do not involve direct confrontation of organized actors (e.g., establishment of rebel headquarters, transfer of military control, peace talks, etc.) and also because ACLED divides multi-day incidents into separate, dated events. Figure 9 shows, moreover, that while both USD and ACLED capture the 2011 uprisings that swept across parts of Africa, this series of events appears much more dramatic in the latter dataset. However, when we only compare lethal events the patterns become nearly identical. This suggests that both datasets capture the most important high-profile events fairly well, and that ACLED's higher event counts are mostly due to its ability to pick up on less lethal and less publicized forms of conflicts.

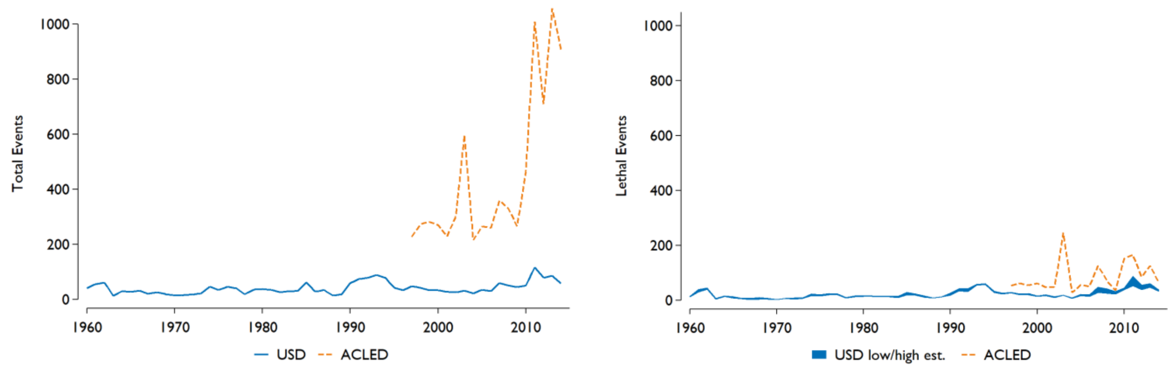

Figure 9. USD vs ACLED

Note: The figure shows trend lines in all types of political violence events for cities that are covered by both datasets (Africa).

The same pattern is found in Figure 10; SCAD indicates a four-fold increase in the frequency of conflict events around the time of the Arab Spring, and it also (like ACLED) suggests another, less severe bump in the early 2000s. In the same way, this difference seems to be mostly a result of SCAD's more extensive reporting on less severe non-lethal events, since when we look only at lethal incidents both datasets report very similar numbers of events.

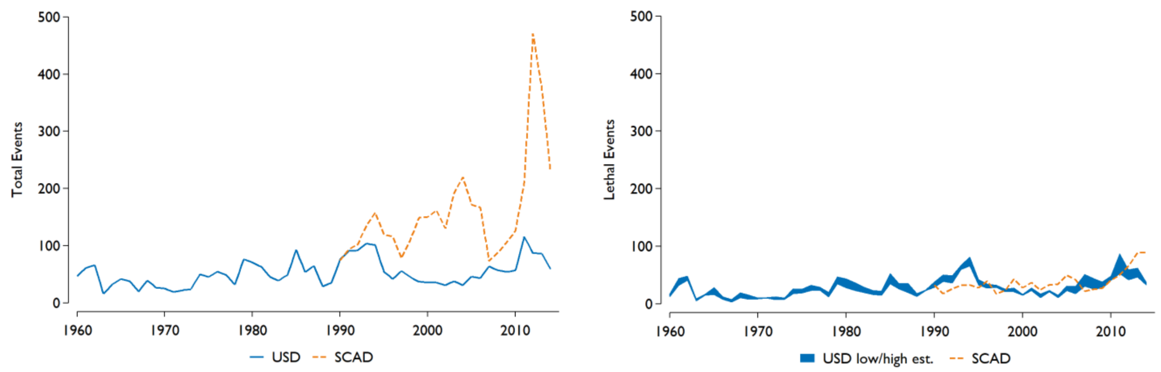

Figure 10. USD vs SCAD

Note: The figure shows trend lines in all types of political violence events for cities that are covered by both datasets (Africa, Mexico, Central America, and Caribbean).

Perhaps somewhat surprisingly, the dataset that best matches the USD in terms of the shape of the overall trend is the UCDP GED, despite the latter being founded on the most stringent and rigorous coding criteria that explicitly excludes unorganized and non-lethal demonstrations and protests. In contrast to the previous datasets, the comparison actually becomes more dissimilar when looking only at lethal events. This suggests that given UCDP GED's more narrow focus on a specific type of event, which by definition must reach a minimum threshold of 1 death, they are able to capture in much finer detail the individual battle clashes which the USD might only report on as aggregated periods of conflict.

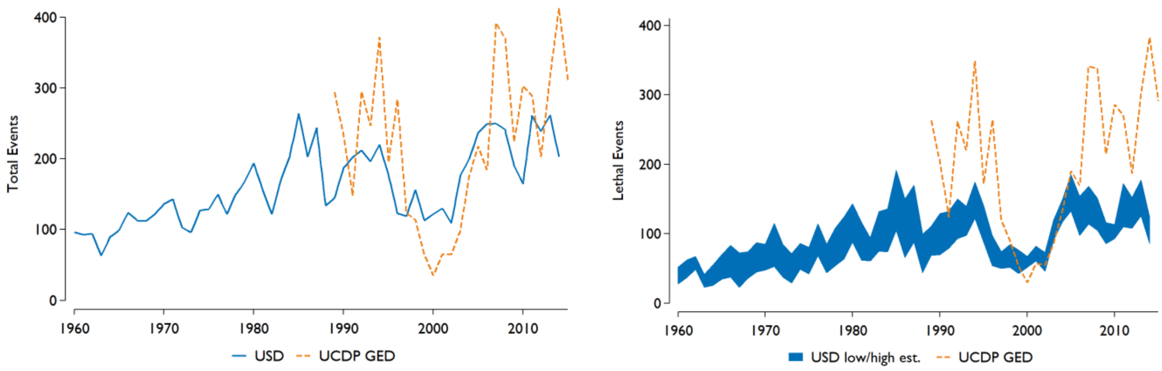

Figure 11. USD vs UCDP GED

Note: The figure shows trend lines in all types of political violence events for cities that are covered by both datasets (Africa, Asia, Latin America, Middle East excl. Damascus).

These comparisons illustrate that while some of the other datasets pick up a higher ratio of small-scale and non-violent types of disorder events, USD does well in consistently capturing the most important events and trends in disorder that cities experience.

5. Urbanization and Disorder: A Reanalysis of Buhaug and Urdal (2013)

Given the significant expansion of the Urban Social Disorder dataset, containing nearly three times as many events in twice as many cities, one may wonder whether results from studies of the first version of the dataset still hold. To find out, we decided to do a replication of Buhaug and Urdal's (2013) analysis of urban population growth and social unrest. The original study tested two hypotheses; for simplicity, we only consider the first one here:

> *H1: High city population growth rates are associated with higher levels of urban social disorder*

The original study found little evidence for such a relationship, and concluded that rapid urbanization in developing countries, in itself, is unlikely to bring more violence and instability in the cities. On the contrary, such urbanization can be seen to relieve the countryside of potentially unsustainable population growth, thereby reducing conflict risk.

In accordance with the original study, we collapse the event data into city-year format with two dependent variables: yearly count of lethal events and yearly count of non-lethal events. The primary explanatory variable is city population growth, calculated as the 5-year moving average annual growth (in percent) based on population statistics from the UN World Urbanization Prospects 2014.[9] The following control variables are included: log-transformed city population size; dummy variables for democratic (Polity > 5) and autocratic (Polity < –5) regime types; log-transformed real GDP per capita data (World Development Indicators); a dummy for economic shock (negative growth in GDP per capita); and ongoing civil conflict in the country (UCDP/PRIO Armed Conflict Dataset). In addition, we include a common time trend to account for a possible temporal bias in reporting and a lagged dependent variable to minimize serially correlated residuals. The models are estimated using negative binomial regression with city fixed-effects.[10]

Table 2 presents the results from the original study exactly as reported in their Models 1a and 1b (Buhaug and Urdal 2013, p. 7) side-by-side with the new results obtained by estimating similarly specified regression models on the expanded USD 2.0 data (here labeled Models 2a and 2b). Despite a near doubling of the sample size, the results for most variables hold up pretty well. Reassuringly, the main finding from the Buhaug and Urdal study – that the frequency of political violence is unrelated to a city's population growth rate – is replicated for lethal as well as non-lethal forms of disorder. However, we do find more support for the notion that very populous cities see unrest more often – in line with the robust population finding for civil war outbreak. Other variable effects vary little between the old and new models and the substantive interpretation of the results are similar.

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[9] These data refer to 'urban agglomerations' and thus count the population of each city's greater metropolitan area. This makes it different from the data used in Buhaug and Urdal (2013), which used UN Demographic Yearbook data limited to stricter inner-city population counts. Even so, the estimates compare well, suggesting sample average population growth rates of 3.55% and 3.58%, respectively.

[10] Due to certain unfortunate properties with the `xtnbreg, fe` approach (Allison and Waterman 2002) we also consider ordinary negative binomial regression with city dummies (Appendix). The results are mostly similar to Table 2.

Whether findings from other studies using the original Urban Social Disorder data are robust to the expansion of the dataset in space and time remains to be determined but the models in Table 2 provide at least indicative evidence that the drivers of urban disorder in Latin America and the Middle East (which are included in v.2.0 only) share commonalities with those taking place in Asia and Sub-Saharan Africa.

Table 2. Original and expanded analysis of urban social disorder

	Original		USD 2.0	
	1a. Lethal	1b. Non-lethal	2a. Lethal	2b. Non-lethal
City population growth	0.017	-0.012	0.002	-0.010
	(0.012)	(0.011)	(0.002)	(0.013)
City population (ln)	0.001	0.105	0.148*	0.218**
	(0.084)	(0.067)	(0.059)	(0.046)
Democracy	-0.324*	-0.017	-0.203*	-0.119
	(0.138)	(0.114)	(0.083)	(0.066)
Autocracy	-0.342**	-0.241**	-0.190*	-0.242**
	(0.100)	(0.089)	(0.082)	(0.068)
GDP capita (ln)	-0.248**	0.056	-0.154**	0.053
	(0.096)	(0.074)	(0.052)	(0.040)
Economic shock	0.220*	0.275**	0.227**	0.182**
	(0.088)	(0.077)	(0.060)	(0.049)
Ongoing civil conflict	0.633**	0.257**	0.805**	0.357**
	(0.104)	(0.091)	(0.072)	(0.058)
Time trend	0.012*	0.001	0.011**	-0.005
	(0.005)	(0.004)	(0.004)	(0.003)
Lagged dependent variable	0.120**	0.098**	0.088**	0.106**
	(0.015)	(0.009)	(0.007)	(0.006)
Constant	0.835	-1.647*	-23.251**	7.974
	(0.873)	(0.668)	(7.003)	(5.580)
Observations	2,185	2,227	4,208	4,379
Number of cities	53	54	95	99

Note: Negative binomial regression estimates with city fixed-effects. S.E. in parentheses. *p<0.05; **p<0.01

6. Conclusion

This paper has presented the new version 2.0 of the PRIO Urban Social Disorder dataset, which now covers 103 major cities across the developing world over the past 55 years. The long time-series is a particularly useful feature of this dataset, making it possible to detect and analyze gradual, long-term changes in dynamics of urban violence. This added value comes at a cost, of course. The dataset is limited to events taking place in capital cities of countries outside the Organization for Economic Co-operation and Development (OECD) world. Besides, relying on Keesing's as the single source of information means that the dataset is bound to have a less exhaustive list of relevant events than data collection efforts that manage to draw on a larger set of local media reports. Even so, the USD dataset offers a useful complement to other conflict event datasets, especially for users interested in longitudinal analysis of political violence as well as non-violent forms of social disorder.

The USD 2.0 dataset is publically available and can be downloaded from PRIO's data portal at https://www.prio.org/data/.

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Appendix: Additional Tables

Table 3. Urbanization and urban social disorder: alternative specification using city dummies

	USD 2.0	
	3a. Lethal	3b. Non-lethal
City population growth	0.002	-0.007
	(0.001)	(0.009)
City population (ln)	0.814**	0.551**
	(0.126)	(0.105)
Democracy	-0.213*	-0.109
	(0.096)	(0.075)
Autocracy	-0.118	-0.140
	(0.095)	(0.080)
GDP capita (ln)	-0.064	0.116
	(0.074)	(0.061)
Economic shock	0.246**	0.258**
	(0.067)	(0.058)
Ongoing civil conflict	0.889**	0.416**
	(0.083)	(0.069)
Time trend	-0.017*	-0.020**
	(0.007)	(0.006)
Lagged dependent variable	0.171**	0.145**
	(0.019)	(0.012)
Constant	27.661*	34.788**
	(12.678)	(10.752)
Observations	4,404	4,404

Note: Negative binomial regression estimates with city dummies. S.E. in parentheses. *p<0.05; **p<0.01.

Table 4. Overview of Cities

Region	City	Country	Total events	Lethal events
Asia	Almaty	Kazakhstan	11	4
Asia	Ashgabat	Turkmenistan	5	2
Asia	Astana	Kazakhstan	0	0
Asia	Baku	Azerbaijan	77	14
Asia	Bangkok	Thailand	152	36
Asia	Beijing	China	116	11
Asia	Bishkek	Kyrgyzstan	22	6
Asia	Calcutta	India	77	36
Asia	Colombo	Sri Lanka	143	78
Asia	Dhaka	Bangladesh	187	60
Asia	Dushanbe	Tajikistan	30	16
Asia	Hanoi	Vietnam	33	22
Asia	Islamabad	Pakistan	98	41
Asia	Jakarta	Indonesia	138	34
Asia	Kabul	Afghanistan	276	195

Asia	Karachi	Pakistan	277	184
Asia	Kathmandu	Nepal	100	26
Asia	Kuala Lumpur	Malaysia	41	10
Asia	Lhasa	China	19	6
Asia	Manila	Philippines	153	56
Asia	Mumbai	India	60	21
Asia	Naypyidaw	Myanmar	2	1
Asia	New Delhi	India	175	54
Asia	Phnom Penh	Cambodia	84	35
Asia	Rangoon	Myanmar	67	21
Asia	Saigon	Vietnam	152	60
Asia	Seoul	South Korea	146	18
Asia	Shanghai	China	36	0
Asia	Singapore	Singapore	4	0
Asia	Taipei	Taiwan	38	1
Asia	Tashkent	Uzbekistan	15	6
Asia	Tbilisi	Georgia	62	15
Asia	Tehran	Iran	261	102
Asia	Tokyo	Japan	64	8
Asia	Ulan Bator	Mongolia	19	2
Asia	Vientiane	Laos	30	11
Asia	Yerevan	Armenia	72	9
Latin America	Asuncion	Paraguay	34	6
Latin America	Bogota	Colombia	117	58
Latin America	Brasilia	Brazil	38	0
Latin America	Buenos Aires	Argentina	238	46
Latin America	Caracas	Venezuela	108	34
Latin America	Guatemala City	Guatemala	93	47
Latin America	Havana	Cuba	28	6
Latin America	La Paz	Bolivia	116	19
Latin America	Lima	Peru	166	42
Latin America	Mexico City	Mexico	65	17
Latin America	Montevideo	Uruguay	76	11
Latin America	Panama City	Panama	46	7
Latin America	Port-Au-Prince	Haiti	107	66
Latin America	Quito	Ecuador	64	15
Latin America	Rio De Janeiro	Brazil	79	26
Latin America	San Jose	Costa Rica	16	1
Latin America	San Salvador	El Salvador	157	68
Latin America	Santiago	Chile	217	53
Latin America	Santo Domingo	Dominican Republic	62	31
Latin America	Sao Paulo	Brazil	68	18
Latin America	Tegucigalpa	Honduras	42	11
Middle East and North Africa	Abu Dhabi	United Arab Emirates	4	2
Middle East and North Africa	Algiers	Algeria	246	150
Middle East and North Africa	Amman	Jordan	61	24

Middle East and North Africa	Ankara	Turkey	138	38
Middle East and North Africa	Baghdad	Iraq	472	387
Middle East and North Africa	Beirut	Lebanon	337	228
Middle East and North Africa	Cairo	Egypt	162	67
Middle East and North Africa	Casablanca	Morocco	15	8
Middle East and North Africa	Damascus	Syria	114	85
Middle East and North Africa	Istanbul	Turkey	234	97
Middle East and North Africa	Kuwait City	Kuwait	27	10
Middle East and North Africa	Rabat	Morocco	56	4
Middle East and North Africa	Riyadh	Saudi Arabia	36	26
Middle East and North Africa	Sanaa	Yemen	125	61
Middle East and North Africa	Tripoli	Libya	66	24
Middle East and North Africa	Tunis	Tunisia	55	13
Sub-Saharan Africa	Abidjan	Cote d'Ivoire	50	22
Sub-Saharan Africa	Abuja	Nigeria	19	10
Sub-Saharan Africa	Accra	Ghana	30	9
Sub-Saharan Africa	Addis Ababa	Ethiopia	74	43
Sub-Saharan Africa	Antananarivo	Madagascar	41	18
Sub-Saharan Africa	Bamako	Mali	20	6
Sub-Saharan Africa	Brazzaville	Congo	38	27
Sub-Saharan Africa	Cape Town	South Africa	83	26
Sub-Saharan Africa	Conakry	Guinea	51	27
Sub-Saharan Africa	Dakar	Senegal	29	11
Sub-Saharan Africa	Dar Es Salaam	Tanzania	9	4
Sub-Saharan Africa	Harare	Zimbabwe	117	30
Sub-Saharan Africa	Johannesburg	South Africa	137	49
Sub-Saharan Africa	Kampala	Uganda	67	37
Sub-Saharan Africa	Khartoum	Sudan	72	24
Sub-Saharan Africa	Kigali	Rwanda	22	18
Sub-Saharan Africa	Kinshasa	Congo, DRC	88	33
Sub-Saharan Africa	Lagos	Nigeria	69	34
Sub-Saharan Africa	Lome	Togo	43	18
Sub-Saharan Africa	Luanda	Angola	40	18
Sub-Saharan Africa	Lusaka	Zambia	36	16
Sub-Saharan Africa	Maputo	Mozambique	32	16
Sub-Saharan Africa	Mogadishu	Somalia	230	180
Sub-Saharan Africa	Monrovia	Liberia	43	29
Sub-Saharan Africa	Nairobi	Kenya	94	40
Sub-Saharan Africa	Ndjamena	Chad	33	20
Sub-Saharan Africa	Niamey	Niger	33	13
Sub-Saharan Africa	Ouagadougou	Burkina Faso	20	7
Sub-Saharan Africa	Yaounde	Cameroon	10	5

Urban Social Disorder: An Update

Unlike most other forms of violent conflict, the rate of urban social disorder events, such as demonstrations and riots, has increased steadily over recent decades. One reason for the diverging trends in political violence may be the demographic shift in the global population. The world is rapidly urbanizing, and the rural-urban migration is especially strong in the developing world, which has historically hosted the large majority of rural-based civil conflicts. Are we witnessing a transformation of violence, where conventional rebel conflicts in the countryside are gradually being replaced by less organized and less predictable forms of urban unrest? This paper presents an updated and expanded version of the PRIO Urban Social Disorder (USD) dataset, covering lethal as well as non-lethal disorder events for national capitals and other major cities across the developing world for all years, 1960–2014. This paper consists of four parts: (i) a description of the new dataset; (ii) a presentation of spatiotemporal trends and patterns in urban violence; (iii) a simple comparison of the USD data with alternative conflict event datasets; and (iv) a replication of an earlier study of urban population growth and social disorder, in order to assess whether past findings are likely to hold up with new data.

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